Try 36 easy

May 6, 2025

[ ]:
```
import os
import random
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras import backend as K
from tensorflow.keras import layers, Model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc, accuracy_score
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'

# Seeds
random.seed(42)
np.random.seed(42)
tf.random.set_seed(42)

# Configuration
IMG_SIZE = (128, 128)
BATCH_SIZE = 32
EPOCHS = 150
DATA_PATH = "/kaggle/input/socofing/SOCOFing/Real/"
ALTER_EASY_PATH = "/kaggle/input/socofing/SOCOFing/Altered/Altered-Easy/"

# Data Loading and Preprocessing
def load_fingerprint_data(data_path):
    images = []
    labels = []

    for filename in os.listdir(data_path):
        if filename.endswith(".BMP"):
            parts = filename.split('__')
            person_id = parts[0]
            finger_info = parts[1].split('_')
```

```
            hand = finger_info[1]
            finger_type = finger_info[2]
            label = f"{person_id}_{hand}_{finger_type}"

            img_path = os.path.join(data_path, filename)
            img = load_img(img_path, color_mode='grayscale',␣
 ↪target_size=IMG_SIZE)
            img = img_to_array(img).astype('float32') / 255.0
            images.append(img)
            labels.append(label)

    images = np.array(images)
    labels = np.array(labels)

    if images.ndim != 4:
        raise ValueError(f"Expected 4D array (num_samples, height, width,␣
 ↪channels), got {images.shape}")

    return images, labels

# Load both datasets
images_real, labels_real = load_fingerprint_data(DATA_PATH)
images_alter_easy, labels_alter_easy = load_fingerprint_data(ALTER_EASY_PATH)
print(f"Loaded {len(images_real)} images from Real dataset")
print(f"Loaded {len(images_alter_easy)} images from Alter-Easy dataset")
print(f"Image shape: {images_real[0].shape}")

# Pair Generation
def create_pairs(images_real, labels_real, images_alter_easy,␣
 ↪labels_alter_easy):
    label_to_real_image = {}
    for img, label in zip(images_real, labels_real):
        label_to_real_image[label] = img

    label_to_alter_images = {}
    for img, label in zip(images_alter_easy, labels_alter_easy):
        if label not in label_to_alter_images:
            label_to_alter_images[label] = []
        label_to_alter_images[label].append(img)

    # Generate positive pairs
    positive_pairs = []
    for label in label_to_real_image:
        if label in label_to_alter_images:
            real_img = label_to_real_image[label]
            for alter_img in label_to_alter_images[label]:
                positive_pairs.append([real_img, alter_img])
```

```
    # Generate negative pairs
    negative_pairs = []
    num_positive = len(positive_pairs)

    common_labels = list(set(label_to_real_image.keys()) &␣
 ↪set(label_to_alter_images.keys()))

    while len(negative_pairs) < num_positive:
        label1 = random.choice(common_labels)
        label2 = random.choice(common_labels)
        if label1 != label2:
            real_img = label_to_real_image[label1]
            alter_img = random.choice(label_to_alter_images[label2])
            negative_pairs.append([real_img, alter_img])

    # Combine and shuffle pairs
    pairs = positive_pairs + negative_pairs
    pair_labels = [1] * len(positive_pairs) + [0] * len(negative_pairs)

    indices = np.arange(len(pairs))
    np.random.shuffle(indices)
    pairs = np.array(pairs)[indices]
    pair_labels = np.array(pair_labels)[indices]

    return pairs, pair_labels

pairs, labels = create_pairs(images_real, labels_real, images_alter_easy,␣
 ↪labels_alter_easy)
print(f"Generated {len(pairs)} pairs")

# Train/Validation/Test Split
X_train, X_temp, y_train, y_temp = train_test_split(
    pairs, labels, train_size=0.7, test_size=0.3, random_state=42,␣
 ↪stratify=labels
)

X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, train_size=0.5, test_size=0.5, random_state=42,␣
 ↪stratify=y_temp
)

print(f"Training pairs: {len(X_train)}")
print(f"Validation pairs: {len(X_val)}")
print(f"Test pairs: {len(X_test)}")
print(f"Training class distribution: {np.bincount(y_train)}")
print(f"Validation class distribution: {np.bincount(y_val)}")
```

```
print(f"Test class distribution: {np.bincount(y_test)}")
```

```
2025-05-05 22:28:18.180481: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1746484098.202392     436 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1746484098.209488     436 cuda_blas.cc:1418] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
```

```
Loaded 6000 images from Real dataset
Loaded 17931 images from Alter-Easy dataset
Image shape: (128, 128, 1)
```

```
I0000 00:00:1746484151.365380     436 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 15513 MB memory:  -> device:
0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04.0, compute capability: 6.0
```

```
Generated 35862 pairs
Training pairs: 25103
Validation pairs: 5379
Test pairs: 5380
Training class distribution: [12551 12552]
Validation class distribution: [2690 2689]
Test class distribution: [2690 2690]
```

[2]:
```
# Siamese Network Architecture
def create_embedding_network(input_shape):
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(32, (5, 5), activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01))(inputs)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(64, (3, 3), activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(128, (3, 3), activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)
```

```
    x = layers.Conv2D(256, (3, 3), activation='relu', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(512, (3, 3), activation='relu', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(256, activation='relu', kernel_regularizer=tf.keras.
↪regularizers.l2(0.01))(x)
    x = layers.Dropout(0.35)(x)
    x = layers.Dense(256, activation=None)(x)

    return Model(inputs, x)

def build_siamese_model(input_shape):
    input_a = layers.Input(shape=input_shape)
    input_b = layers.Input(shape=input_shape)

    embedding_network = create_embedding_network(input_shape)

    embedding_a = embedding_network(input_a)
    embedding_b = embedding_network(input_b)

    distance = layers.Lambda(
        lambda embeddings: tf.abs(embeddings[0] - embeddings[1])
    )([embedding_a, embedding_b])

    output = layers.Dense(1, activation='sigmoid')(distance)

    return Model(inputs=[input_a, input_b], outputs=output)

input_shape = IMG_SIZE + (1,)
siamese_model = build_siamese_model(input_shape)
siamese_model.summary()

# Compile the model
siamese_model.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

# Training
early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True)
```

```
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5,␣
↪min_lr=1e-6)
checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss',␣
↪save_best_only=True)
```

```
Model: "functional_1"


 Layer (type)                 Output Shape                  Param #  Connected␣
↪to

 input_layer (InputLayer)     (None, 128, 128, 1)                 0  -         ␣
↪

 input_layer_1                (None, 128, 128, 1)                 0  -         ␣
↪
 (InputLayer)                                                                  ␣
↪

 functional (Functional)      (None, 256)                 1,769,600  ␣
↪input_layer[0][0],
                                                                     ␣
↪input_layer_1[0][0]

 lambda (Lambda)              (None, 256)                         0  ␣
↪functional[0][0],
                                                                     ␣
↪functional[1][0]

 dense_2 (Dense)              (None, 1)                         257  ␣
↪lambda[0][0]


 Total params: 1,769,857 (6.75 MB)

 Trainable params: 1,767,873 (6.74 MB)

 Non-trainable params: 1,984 (7.75 KB)
```

[3]:
```
history = siamese_model.fit(
    [X_train[:, 0], X_train[:, 1]],
    y_train,
    validation_data=([X_val[:, 0], X_val[:, 1]], y_val),
    batch_size=BATCH_SIZE,
```

```
    epochs=EPOCHS,
    callbacks=[early_stopping, reduce_lr, checkpoint]
)

K.clear_session()
tf.compat.v1.reset_default_graph()

# Training Curves
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.savefig('/kaggle/working/training_curves.png')
plt.show()

# Model Evaluation
def evaluate_model(model, X, y, set_name=''):
    batch_size = 8
    y_pred = []
    for i in range(0, len(X), batch_size):
        batch_X = X[i:i + batch_size]
        batch_pred = model.predict([batch_X[:, 0], batch_X[:, 1]],␣
↪batch_size=batch_size, verbose=0)
        y_pred.extend(batch_pred)
    y_pred = np.array(y_pred)
    fpr, tpr, thresholds = roc_curve(y, y_pred)
    roc_auc = auc(fpr, tpr)

    plt.figure()
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =␣
↪{roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
```

```python
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic ({set_name})')
    plt.legend(loc="lower right")
    plt.savefig(f'/kaggle/working/roc_curve_{set_name.lower()}.png')
    plt.show()

    return roc_auc

print("Training Evaluation:")
train_auc = evaluate_model(siamese_model, X_train, y_train, 'Training')

print("\nValidation Evaluation:")
val_auc = evaluate_model(siamese_model, X_val, y_val, 'Validation')

print("\nTest Evaluation:")
test_auc = evaluate_model(siamese_model, X_test, y_test, 'Test')

train_acc = history.history['accuracy'][-1]
val_acc = history.history['val_accuracy'][-1]
test_acc = siamese_model.evaluate([X_test[:, 0], X_test[:, 1]], y_test)[1]

print(f"\nFinal Metrics:")
print(f"Training Accuracy: {train_acc:.4f} | AUC: {train_auc:.4f}")
print(f"Validation Accuracy: {val_acc:.4f} | AUC: {val_auc:.4f}")
print(f"Test Accuracy: {test_acc:.4f} | AUC: {test_auc:.4f}")

# Real Photo Evaluation
def visualize_predictions(model, X, y, num_samples=5):
    indices = np.random.choice(len(X), num_samples)
    sample_pairs = X[indices]
    sample_labels = y[indices]

    predictions = model.predict([sample_pairs[:, 0], sample_pairs[:, 1]])

    plt.figure(figsize=(15, 5))
    for i in range(num_samples):
        plt.subplot(2, num_samples, i+1)
        plt.imshow(sample_pairs[i][0].squeeze(), cmap='gray')
        plt.title(f"Label: {sample_labels[i]}\nPred: {predictions[i][0]:.2f}")
        plt.axis('off')

        plt.subplot(2, num_samples, i+1+num_samples)
        plt.imshow(sample_pairs[i][1].squeeze(), cmap='gray')
        plt.axis('off')

    plt.tight_layout()
```

```python
    plt.show()

print("Sample Test Predictions:")
visualize_predictions(siamese_model, X_test, y_test)
```

```
Epoch 1/150

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1746484172.874423     468 service.cc:148] XLA service 0x7a4e8c01d990
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1746484172.874825     468 service.cc:156]   StreamExecutor device
(0): Tesla P100-PCIE-16GB, Compute Capability 6.0
I0000 00:00:1746484173.625019     468 cuda_dnn.cc:529] Loaded cuDNN version
90300

  7/785             17s 22ms/step - accuracy:
0.5496 - loss: 10.5390

I0000 00:00:1746484179.288907     468 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

785/785             41s 35ms/step -
accuracy: 0.8686 - loss: 3.8498 - val_accuracy: 0.7747 - val_loss: 0.7871 -
learning_rate: 0.0010
Epoch 2/150
785/785             18s 22ms/step -
accuracy: 0.9237 - loss: 0.5956 - val_accuracy: 0.8991 - val_loss: 0.7238 -
learning_rate: 0.0010
Epoch 3/150
785/785             17s 22ms/step -
accuracy: 0.9330 - loss: 0.5545 - val_accuracy: 0.8241 - val_loss: 0.9546 -
learning_rate: 0.0010
Epoch 4/150
785/785             17s 22ms/step -
accuracy: 0.9287 - loss: 0.6490 - val_accuracy: 0.7816 - val_loss: 0.9169 -
learning_rate: 0.0010
Epoch 5/150
785/785             18s 22ms/step -
accuracy: 0.9281 - loss: 0.6106 - val_accuracy: 0.9214 - val_loss: 0.6560 -
learning_rate: 0.0010
Epoch 6/150
785/785             17s 22ms/step -
accuracy: 0.9429 - loss: 0.4909 - val_accuracy: 0.9201 - val_loss: 0.5510 -
learning_rate: 0.0010
Epoch 7/150
785/785             17s 22ms/step -
accuracy: 0.9481 - loss: 0.4764 - val_accuracy: 0.9124 - val_loss: 0.6225 -
learning_rate: 0.0010
```

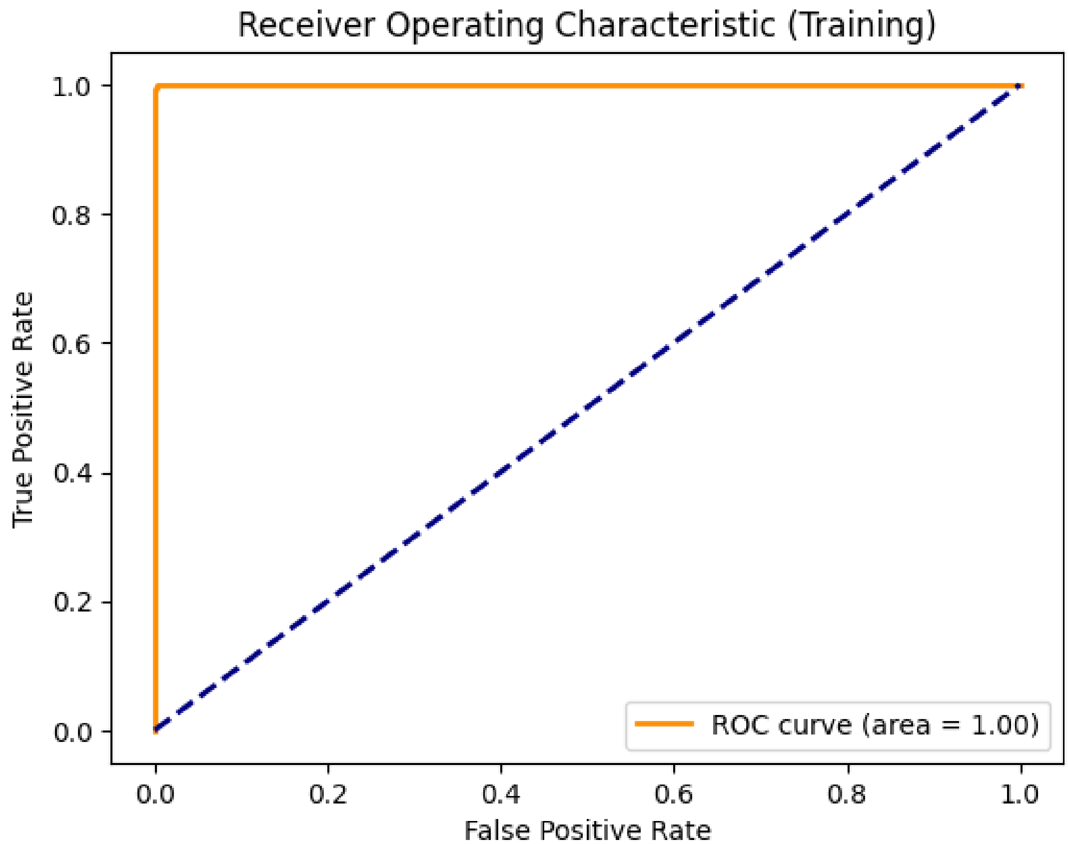
```
Epoch 8/150
785/785              17s 22ms/step -
accuracy: 0.9415 - loss: 0.5362 - val_accuracy: 0.9020 - val_loss: 0.6076 -
learning_rate: 0.0010
Epoch 9/150
785/785              17s 22ms/step -
accuracy: 0.9441 - loss: 0.4999 - val_accuracy: 0.9334 - val_loss: 0.4930 -
learning_rate: 0.0010
Epoch 10/150
785/785              17s 22ms/step -
accuracy: 0.9479 - loss: 0.4553 - val_accuracy: 0.9167 - val_loss: 0.4833 -
learning_rate: 0.0010
Epoch 11/150
785/785              17s 22ms/step -
accuracy: 0.9488 - loss: 0.4634 - val_accuracy: 0.9855 - val_loss: 0.4319 -
learning_rate: 0.0010
Epoch 12/150
785/785              17s 22ms/step -
accuracy: 0.9509 - loss: 0.4602 - val_accuracy: 0.9413 - val_loss: 0.4734 -
learning_rate: 0.0010
Epoch 13/150
785/785              17s 22ms/step -
accuracy: 0.9505 - loss: 0.4511 - val_accuracy: 0.9446 - val_loss: 0.4268 -
learning_rate: 0.0010
Epoch 14/150
785/785              17s 22ms/step -
accuracy: 0.9515 - loss: 0.4256 - val_accuracy: 0.9836 - val_loss: 0.3512 -
learning_rate: 0.0010
Epoch 15/150
785/785              17s 22ms/step -
accuracy: 0.9492 - loss: 0.4365 - val_accuracy: 0.9807 - val_loss: 0.3460 -
learning_rate: 0.0010
Epoch 16/150
785/785              17s 22ms/step -
accuracy: 0.9567 - loss: 0.3981 - val_accuracy: 0.9823 - val_loss: 0.3813 -
learning_rate: 0.0010
Epoch 17/150
785/785              17s 22ms/step -
accuracy: 0.9582 - loss: 0.3835 - val_accuracy: 0.9221 - val_loss: 0.6166 -
learning_rate: 0.0010
Epoch 18/150
785/785              17s 22ms/step -
accuracy: 0.9568 - loss: 0.3888 - val_accuracy: 0.9842 - val_loss: 0.3666 -
learning_rate: 0.0010
Epoch 19/150
785/785              17s 22ms/step -
accuracy: 0.9560 - loss: 0.3765 - val_accuracy: 0.9822 - val_loss: 0.3903 -
learning_rate: 0.0010
```

```
Epoch 20/150
785/785              17s 22ms/step -
accuracy: 0.9547 - loss: 0.3963 - val_accuracy: 0.9175 - val_loss: 0.5846 -
learning_rate: 0.0010
Epoch 21/150
785/785              17s 22ms/step -
accuracy: 0.9635 - loss: 0.3134 - val_accuracy: 0.9734 - val_loss: 0.1937 -
learning_rate: 2.0000e-04
Epoch 22/150
785/785              17s 22ms/step -
accuracy: 0.9724 - loss: 0.1639 - val_accuracy: 0.9630 - val_loss: 0.1995 -
learning_rate: 2.0000e-04
Epoch 23/150
785/785              17s 22ms/step -
accuracy: 0.9696 - loss: 0.1594 - val_accuracy: 0.9740 - val_loss: 0.1784 -
learning_rate: 2.0000e-04
Epoch 24/150
785/785              17s 22ms/step -
accuracy: 0.9715 - loss: 0.1494 - val_accuracy: 0.9820 - val_loss: 0.1538 -
learning_rate: 2.0000e-04
Epoch 25/150
785/785              17s 22ms/step -
accuracy: 0.9742 - loss: 0.1355 - val_accuracy: 0.9693 - val_loss: 0.1796 -
learning_rate: 2.0000e-04
Epoch 26/150
785/785              17s 22ms/step -
accuracy: 0.9745 - loss: 0.1383 - val_accuracy: 0.9686 - val_loss: 0.1730 -
learning_rate: 2.0000e-04
Epoch 27/150
785/785              17s 22ms/step -
accuracy: 0.9727 - loss: 0.1414 - val_accuracy: 0.9894 - val_loss: 0.1288 -
learning_rate: 2.0000e-04
Epoch 28/150
785/785              17s 22ms/step -
accuracy: 0.9783 - loss: 0.1283 - val_accuracy: 0.9872 - val_loss: 0.1395 -
learning_rate: 2.0000e-04
Epoch 29/150
785/785              17s 22ms/step -
accuracy: 0.9761 - loss: 0.1311 - val_accuracy: 0.9894 - val_loss: 0.1448 -
learning_rate: 2.0000e-04
Epoch 30/150
785/785              17s 22ms/step -
accuracy: 0.9767 - loss: 0.1376 - val_accuracy: 0.9797 - val_loss: 0.1499 -
learning_rate: 2.0000e-04
Epoch 31/150
785/785              17s 22ms/step -
accuracy: 0.9754 - loss: 0.1296 - val_accuracy: 0.9708 - val_loss: 0.1703 -
learning_rate: 2.0000e-04
```

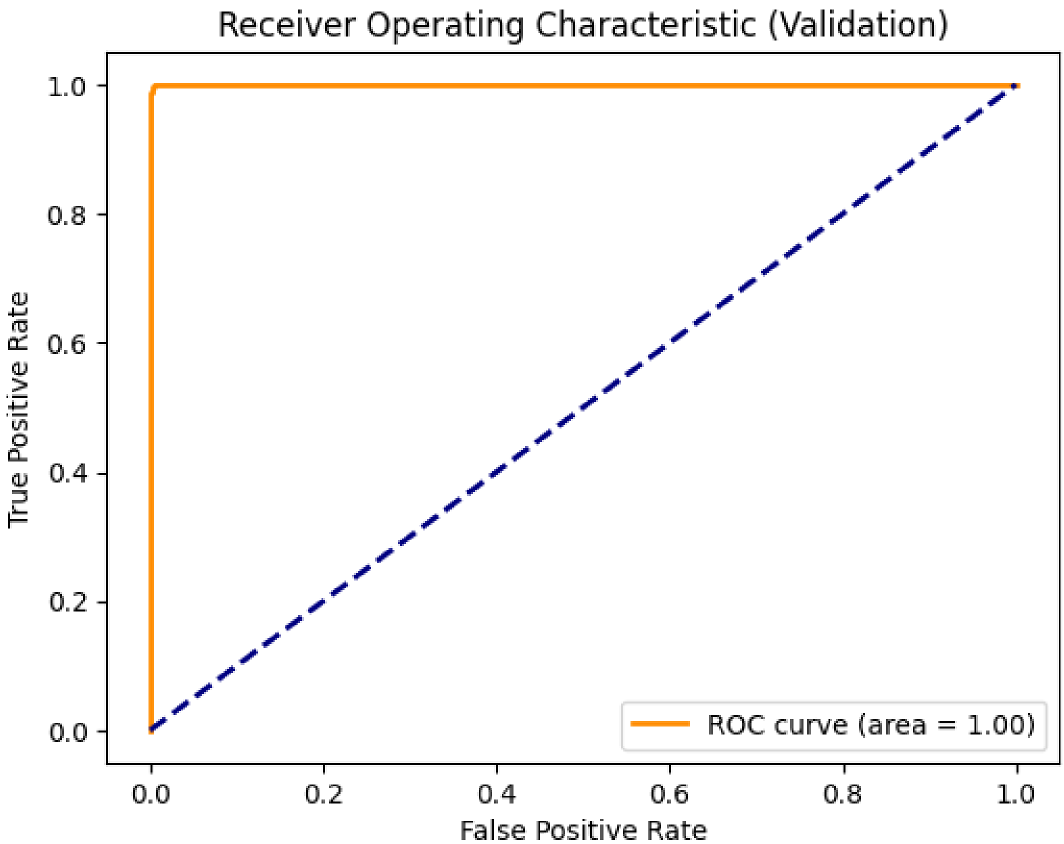
```
Epoch 32/150
785/785              17s 22ms/step -
accuracy: 0.9678 - loss: 0.1679 - val_accuracy: 0.9892 - val_loss: 0.1396 -
learning_rate: 2.0000e-04
Epoch 33/150
785/785              17s 22ms/step -
accuracy: 0.9792 - loss: 0.1235 - val_accuracy: 0.9870 - val_loss: 0.1228 -
learning_rate: 4.0000e-05
Epoch 34/150
785/785              17s 22ms/step -
accuracy: 0.9832 - loss: 0.0960 - val_accuracy: 0.9883 - val_loss: 0.1103 -
learning_rate: 4.0000e-05
Epoch 35/150
785/785              17s 22ms/step -
accuracy: 0.9849 - loss: 0.0858 - val_accuracy: 0.9894 - val_loss: 0.1020 -
learning_rate: 4.0000e-05
Epoch 36/150
785/785              17s 22ms/step -
accuracy: 0.9832 - loss: 0.0815 - val_accuracy: 0.9872 - val_loss: 0.1055 -
learning_rate: 4.0000e-05
Epoch 37/150
785/785              17s 22ms/step -
accuracy: 0.9845 - loss: 0.0765 - val_accuracy: 0.9861 - val_loss: 0.1095 -
learning_rate: 4.0000e-05
Epoch 38/150
785/785              17s 22ms/step -
accuracy: 0.9849 - loss: 0.0766 - val_accuracy: 0.9822 - val_loss: 0.1141 -
learning_rate: 4.0000e-05
Epoch 39/150
785/785              17s 22ms/step -
accuracy: 0.9857 - loss: 0.0735 - val_accuracy: 0.9874 - val_loss: 0.1038 -
learning_rate: 4.0000e-05
Epoch 40/150
785/785              17s 22ms/step -
accuracy: 0.9876 - loss: 0.0677 - val_accuracy: 0.9853 - val_loss: 0.1079 -
learning_rate: 4.0000e-05
Epoch 41/150
785/785              17s 22ms/step -
accuracy: 0.9896 - loss: 0.0632 - val_accuracy: 0.9849 - val_loss: 0.1081 -
learning_rate: 8.0000e-06
Epoch 42/150
785/785              17s 22ms/step -
accuracy: 0.9912 - loss: 0.0584 - val_accuracy: 0.9853 - val_loss: 0.1040 -
learning_rate: 8.0000e-06
Epoch 43/150
785/785              17s 22ms/step -
accuracy: 0.9909 - loss: 0.0574 - val_accuracy: 0.9846 - val_loss: 0.1064 -
learning_rate: 8.0000e-06
```

```
Epoch 44/150
785/785             17s 22ms/step -
accuracy: 0.9915 - loss: 0.0563 - val_accuracy: 0.9848 - val_loss: 0.1059 -
learning_rate: 8.0000e-06
Epoch 45/150
785/785             17s 22ms/step -
accuracy: 0.9918 - loss: 0.0539 - val_accuracy: 0.9853 - val_loss: 0.1068 -
learning_rate: 8.0000e-06
```

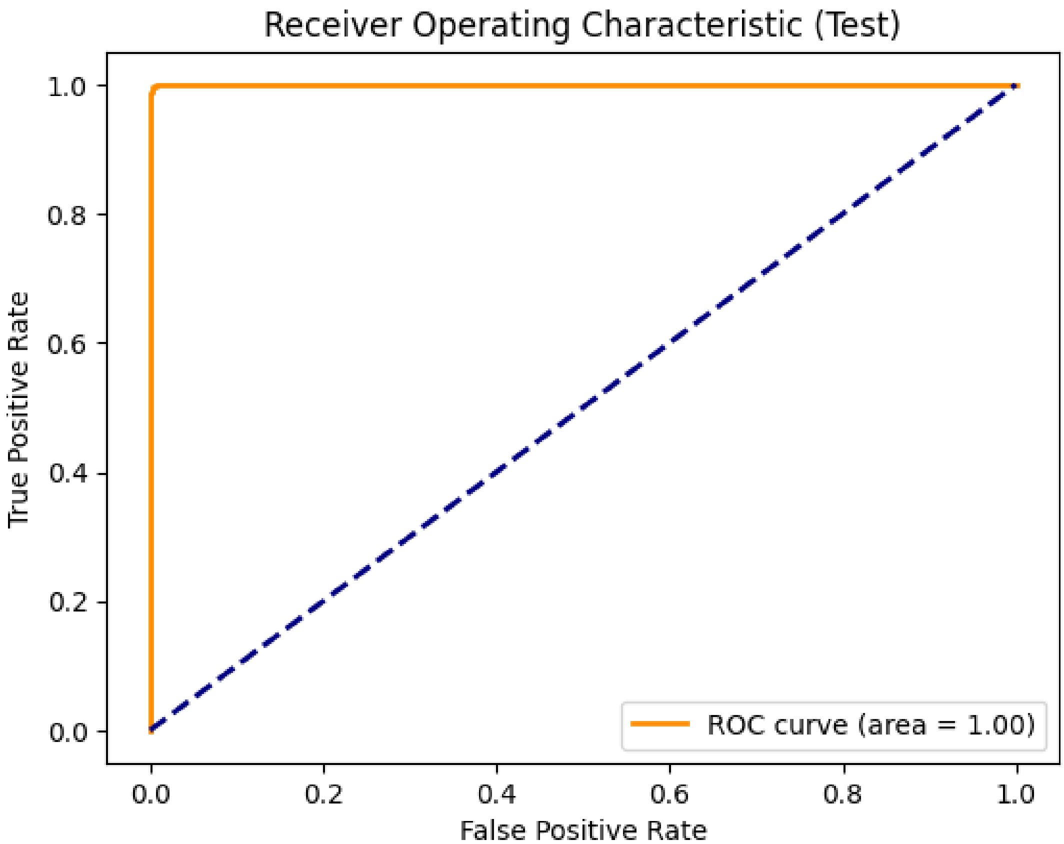

```
Training Evaluation:
```




```
Validation Evaluation:
```



Test Evaluation:




```
169/169              2s 10ms/step -
accuracy: 0.9928 - loss: 0.0991

Final Metrics:
Training Accuracy: 0.9922 | AUC: 1.0000
Validation Accuracy: 0.9853 | AUC: 0.9999
Test Accuracy: 0.9913 | AUC: 0.9999
Sample Test Predictions:
1/1              1s 601ms/step
```


Label: 0
Pred: 0.00
Label: 1
Pred: 0.94
Label: 0
Pred: 0.00
Label: 0
Pred: 0.00
Label: 0
Pred: 0.00